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Multi-Factor, Multi-Indicator Approach to
Asset Pricing: Methods and Empirical Evidence

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Multi-Factor, Multi-Indicator Approach to
Asset Pricing: Methods and Empirical Evidence

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Abstract

We have proposed a multi-factor, multi-indicator approach to test the CAPM and the APT. This approach is able to solve the measuring problem in the market portfolio in testing the CAPM; and it is also able to directly test the APT by linking the common factors to the macroeconomic indicators. Our results from testing the CAPM support Stambough's [1982] argument that the inference about the tests of the CAPM is insensitive to alternative market indexes. The results from testing the APT indicate that it is a one-factor model during 1963-72, while it is a two-factor model during 1973-82. Furthermore, the market variables (including the market portfolio and the transaction volume) play a major role in the pricing relation.

MULTI-FACTOR, MULTI-INDICATOR APPROACH TO ASSET PRICING: METHODS AND EMPIRICAL EVIDENCE

I. Introduction

Roll [1977] has shown that the CAPM can never be tested unless the market portfolio is capable of being measured and identified. However, the market portfolio is actually unobservable. Stated differently, since the market portfolio is subject to measurement error, Sharpe [1964], Lintner [1965] and Mossin [1966] type of capital asset pricing model (CAPM) can never be tested directly. On the other hand, the test of Ross's [1976, 1977] Arbitrage Pricing Theory (APT) does not rely upon the identifications of the market portfolio or the true factors. Nevertheless, Shanken [1982] argues that Ross's contention that the APT is inherently more easily tested is questionable. If we can directly link these unobservable factors to some observable indicators, the Shanken criticism of the test of the APT can be avoided or reduced. Fortunately, a mulitple indicators and multiple causes (MIMIC) model, proposed by Zellner [1970], Goldberg [1972a, 1972b], Jöreskog and Goldberg [1975] and others, is an attractive methodology in dealing with this problem of unobservable variables. This MIMIC model displays a mixture of econometric and factor analysis themes. This concept has successfully been used to test economic models (Turnovsky [1970], Lahiri [1976]). However, the MIMIC model has not been used in capital asset pricing determination.

The purpose of this paper is twofold: (i) to use the MIMIC model to re-examine the CAPM; and (ii) to use the MIMIC model to investigate the relationship between the factors in the APT and the macroeconomic indicators directly. The APT is attractive to both academicians and practitioners, because the model allows more than one factor. To date the practical applications of the APT are still limited, since previous studies in testing the model do not directly link the factors to the indicators. If the linkage between the factors and the indicators can be derived, practical applications will be much improved. The outline of this paper is as follows.

In Section II, the MIMIC model is reviewed and the CAPM and the APT in terms of the MIMIC model are demonstrated. Section III shows how MIMIC can be used to test the CAPM, and Section IV investigates the MIMIC APT. Finally, a brief summary is contained in Section V.

II. The MIMIC Model and the Tests of the CAPM and the APT[1]

II.1 The MIMIC Model

Suppose that a system has k unobservable latent variables $z = (z_1,\ldots,z_k)'$, p observable exogenous indicators $x = (x_1,\ldots,x_p)'$, and m observable endogenous variables $y = (y_1,\ldots,y_m)'$. The specification of this extended MIMIC model of Jöreskog and Goldberger [1975] is as follows. The latent factors z are linearly determined, subject to disturbances $e = (e_1,\ldots,e_k)'$, by observable exogenous indicators x:[2]

$$z = ax + e \tag{1}$$

where

$$a = \begin{bmatrix} a_{11},\ldots,a_{1p} \\ \vdots \quad\quad \vdots \\ a_{k1},\ldots,a_{kp} \end{bmatrix}$$ is a kxp matrix.

In addition, the latent factors z linearly determine the components of endogenous variables y, subject to disturbances $u = (u_1,\ldots,u_m)'$:

$$y = bz + u \tag{2}$$

where

$$b = \begin{bmatrix} b_{11},\ldots,b_{1k} \\ \vdots \quad\quad \vdots \\ b_{m1},\ldots,b_{mk} \end{bmatrix} \text{ is an mxk matrix.}$$

The disturbances are assumed to be mutually independent and normally disturbed with mean zero, namely, $e \sim N(0,\Sigma)$, $u \sim N(0,\Theta^2)$, where $\Sigma = \mathrm{diag}(\sigma_1^2,\ldots,\sigma_k^2)$ and $\Theta^2 = \mathrm{diag}(\theta_1^2,\ldots,\theta_m^2)$. For convenience, all variables are taken to have mean zero. The system of equations (1) and (2) are shown in Figure 1.

Solving the equation systems of (1) and (2), we have the following reduced-form connecting the observable variables:

$$y = bax + be + u = hx + v \tag{3}$$

where the reduced-form coefficient matrix is

$$h = ba \tag{4}$$

and the reduced-form disturbance matrix is

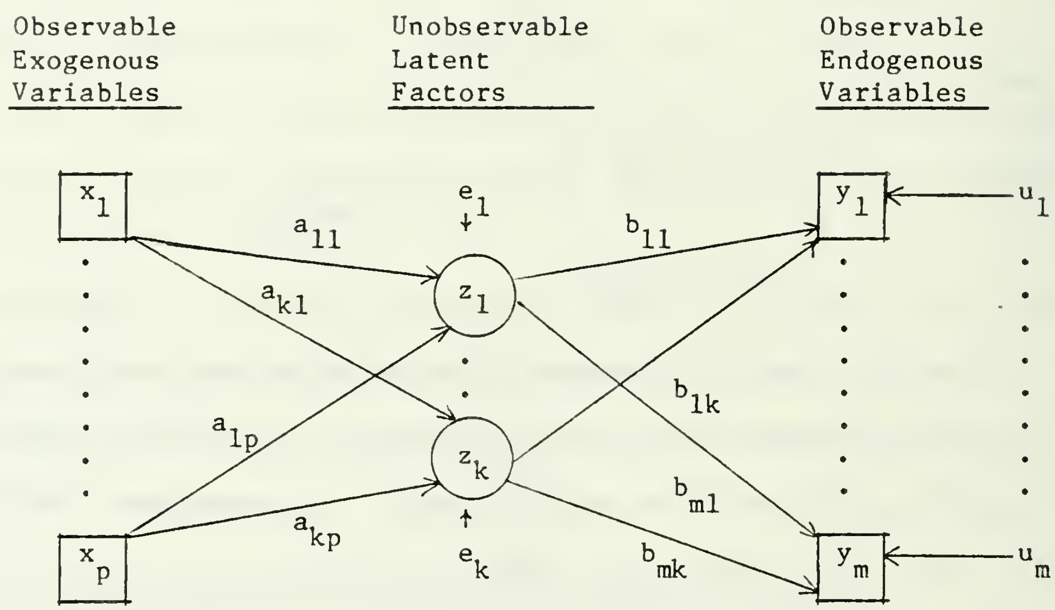
$$v = be + u \tag{5}$$

which has a covariance matrix of

$$\begin{aligned} \Omega &= E(vv') = E[(be + u)(be + u)'] \\ &= b\Sigma b' + \Theta^2 \end{aligned} \tag{6}$$

Figure 1

Multiple Causes and Indicators of Unobservable Variables



where E represents expectation operator.

There are two types of restrictions on the reduced-form: (i) the mxp regression coefficient matrix h has rank k, the mp components of h being expressed in terms of kp + mk elements of a and b, (ii) the mxm residual covariance matrix Ω satisfies a factor analysis model with k common factors, the m(m+1)/2 distinct elements of Ω being expressed in terms of the k + km + m elements of σ^2, b and Θ^2. The first restriction, which is the same as the simultaneous equation models, is familiar to econometricians. The second restriction, which is the same as the factor analysis models, is familiar to psychometricians. In equation (5), e, b and u are regarded as the common factors, the factor loadings and the unique disturbances in the factor analysis model respectively.

We observe that the reduced-form parameters remain unchanged, when any column, say j, of b is multiplied by a scalar and the jth row of a and σ_j are both divided by the same scalar. To remove this indeterminancy of the model, we can normalize the model through (i) σ^2, or (ii) b, or (iii) a. After normalization, the Maximum Likelihood Estimation (MLE) procedure can be used to obtain consistent estimators of the elements in parameters a, b, and Θ^2 (see Attfield [1982], Chen [1981], Jöreskog and Goldberger [1975] and others). In the following, we demonstrate how to apply this MIMIC model to test the CAPM and the APT.

II.2 <u>The Testing Model of the CAPM by the MIMIC Approach</u>

The CAPM can be rewritten, in terms of MIMIC model, as follows:

$$\begin{aligned} \tilde{r}_i &= \beta_i \tilde{r}^*_m + \tilde{u}_i \qquad i = 1,\ldots,N \qquad (7) \\ \tilde{r}^*_m &= \tilde{r}_m + \tilde{e}_m, \end{aligned}$$

where

$\tilde{r}_i$ = the realized excess return (total return less risk-free rate) on security i in a deviation form,

$\tilde{r}_m$ = the realized excess return of the NYSE composite index, and

$\tilde{r}^*_m$ = the unobservable excess return on the market portfolio.

In this special one factor case, we remove the indeterminancy by setting the coefficient on $\tilde{r}_m$ equal to one. Equation (7) is a simultaneous equation model. There are N equations linking the individual security (or portfolio) return to the unobservable true market return, and one equation linking the unobservable true market portfolio return to the realized return of the NYSE composite index. After obtaining the estimated betas from simultaneous equation system of (7), a cross sectional regression of the security return against its risk (β) will be used to test the CAPM or to estimate the riskless rate and the market risk premium as follows:

$$r_{it} = \hat{a}_{0t} + \hat{a}_{1t}\beta_i \tag{8}$$

where

r_{it} = the excess return on security i at time t,

$\hat{a}_{0t}$ = the estimate of the intercept which is supposed to be zero, and

$\hat{a}_{1t}$ = the estimate of the market risk premium.

Four different estimation procedures will be used to estimate equation (8). They are: (i) stationary OLS, (ii) nonstationary OLS, (iii) GLS and (iv) MLE.[3]

II.3 The Testing Model of the APT by the MIMIC Approach

The testing model of the APT, in terms of the MIMIC model, can be rewritten as follows:

$$\begin{aligned} \tilde{r}_i &= b_{i1}\tilde{f}_1 + \ldots + b_{ik}\tilde{f}_k + \tilde{u}_i, \qquad (i = 1,\ldots,N) \\ \tilde{f}_j &= a_{j1}\tilde{I}_1 + \ldots + a_{jp}\tilde{I}_p + \tilde{e}_j, \qquad (j = 1,\ldots,k) \end{aligned} \tag{9}$$

where $\tilde{f}_j$ = the jth unobservable factor, and

$\tilde{I}_h$ = the hth macroeconomic indicator, $h = 1,\ldots,p$.

For convenience and easy explanation, each factor $\tilde{f}$ is assumed to have different set of explained indicators $\tilde{I}$'s. Note that there are N return equations plus k factor equations in the simultaneous equation system (9). The LISREL computer program of Jöreskog and Sörbon [1981] is used to estimate the parameters, a and b, in equation (9). A cross sectional regression is also used to test the APT and to estimate the riskless rate and the factor risk premia by regressing the security return against its risks, b's. The a's coefficients in equation (9) can be used to explain the relationship between factors and indicators.

III. Tests of the CAPM

This section tests the CAPM using the market model and the MIMIC model described in Section II. The objective is to investigate whether the MIMIC method yields a different inference from the market model. Nineteen industry common stock portfolios are formed with the same manner used by MacBeth [1975], Schipper and Thompson [1981] and Stambough [1982].[4] The return on a portfolio is the arithmetic average of returns for firms on the CRSP monthly tape with the appropriate two-digit SEC code for the given month. The tests use returns from the period 1963-1982, and this total period is divided into two equal subperiods: (i) subperiod 1, 1963-1972, and (ii) subperiod 2, 1973-1982. Portfolios are formed primarily because they provide a convenient way to limit the computational dimensions of the MIMIC method. As mentioned by Stambough [1982], industry portfolios also allow rejection of the CAPM due to the presence of additional industry-related variables in the risk-return relation.

Table 1 indicates the number of securities in each portfolio, the SEC codes and betas calculated from the market model and also from the MIMIC model. When the MIMIC model was used to estimate betas by the portfolio excess returns in subperiod 1, convergent problems were encountered during minimization so that the result is inappropriate. Consequently, raw returns in deviation form on the portfolios are used to estimate betas for subperiod 1. The betas estimated from the MIMIC model are very close to those from the market model in both periods. This evidence supports Stambough's discovery that inferences about the CAPM are very insensitive to alternative market indexes.

Table 2 presents return-risk trade-off from the cross sectional relationship in which the average monthly excess portfolio returns (monthly portfolio returns less monthly return on three-month Treasury bills) is regressed on a beta estimated either from the MIMIC model or the market model from two different 120 month periods. Four different estimation procedures are used to estimate the intercepts and the market risk premia. The OLS method presents two sets of t-statistics shown in the

Table 1

Industry portfolio SEC codes, number of firms and estimated betas

Portfolio description	SEC code	# of firms 12/72	# of firms 12/82	Estimated betas* Period 1		Estimated betas* Period 2	
1. Mining	10-14	56	71	1.056	1.009	0.922	0.916
2. Food & beverages	20	75	51	0.894	0.841	0.803	0.803
3. Textile & apparel	22,23	58	45	1.264	1.220	1.081	1.082
4. Paper products	26	30	30	1.030	1.029	0.910	0.909
5. Chemical	28	87	83	0.949	0.947	0.847	0.846
6. Petroleum	29	28	22	0.706	0.792	0.745	0.740
7. Stone, clay, glass	32	43	31	1.050	1.106	1.045	1.045
8. Primary metals	33	56	49	1.136	1.193	0.932	0.930
9. Fabricated metals	34	45	46	1.145	1.155	1.102	1.102
10. Machinery	35	93	104	1.234	1.231	1.104	1.104
11. Appliance & elec. equip.	36	87	82	1.384	1.401	1.179	1.180
12. Transpor. equip.	37	64	50	1.209	1.275	1.150	1.151
13. Misc. manufactrng	38,39	64	59	1.375	1.314	1.197	1.198
14. Railroads	40	18	11	1.294	1.229	0.899	0.895
15. Other transport.	41,42,44 45,47	34	35	1.335	1.447	1.203	1.203
16. Utilities	49	138	152	0.443	0.467	0.564	0.562
17. Department stores	53	35	28	1.149	1.104	1.125	1.125
18. Other retail trades	50-52, 54-59	103	97	1.144	1.088	1.123	1.124
19. Banking, finance, real estate	60-67	184	240	0.968	1.021	1.069	1.068

*The betas shown in the first column are estimated from the market model, while those in the second column are estimated from the MIMIC model.

Table 2

Return-risk cross sectional relationships of the CAPM: 1963-1982

Procedure	Panel A: MIMIC model a_0	a_1	$\bar{R}^2$	Panel B: Market model a_0	a_1	$\bar{R}^2$
			Period 1: 1963-1972			
OLS	.159	.539	.258	.187	.516	.243
(S)	(.71)	(2.70)*		(.85)	(2.61)*	
(NS)	(.41)	(1.03)		(.48)	(1.02)	
GLS	.029	.660		.095	.599	
	(.06)	(1.29)		(.19)	(1.22)	
MLE	-.106	.793		-.082	.770	
	(-.24)	(1.29)		(-.13)	(1.22)	
			Period 2: 1973-1982			
OLS	.370	.266	-.004	.363	.273	-.001
(S)	(1.33)	(.97)		(1.29)	(.99)	
(NS)	(.60)	(.31)		(.59)	(.32)	
GLS	.106	.532		.107	.531	
	(.24)	(.71)		(.24)	(.71)	
MLE	.081	.556		.081	.556	
	(.17)	(.71)		(.17)	(.71)	

Note: The monthly returns are multiplied by 100 before regressing.
* = significant at the 5% level.

The OLS (S) version corresponds to the regression

$$\bar{R}_i - \bar{R}_f = a_0 + a_1 \beta_i + \tilde{e}_i, \quad i=1,\ldots,N.$$

The other versions correspond to the regression

$$R_{it} - R_{ft} = a_{0t} + a_{1t} \beta_i + \tilde{e}_{it}, \quad i=1,\ldots,N,\ t=1,\ldots,T,$$

and the reported coefficients are arithmetic average of the time series $\{a_{0t}, a_{1t};\ t=1,\ldots,T\}$, while t-statistics are in parentheses under each relevant coefficient.

parentheses under the same relevant regression coefficients. The first set (denoted S) assumes that the regression coefficients are constant or stationary over each 120 month period. The second set (denoted NS) of the OLS t-statistics allows the non-stationarities of the regression coefficients by computing the cross sectional regression coefficients in each month and deriving the appropriate standard errors from the time series 120 estimates of the OLS regression coefficients. The GLS and MLE methods also permit the nonstationary coefficients. Thus, their t-statistics are derived from the same procedure in the OLS NS method. Although the OLS and the GLS estimators are biased and inconsistent due to measurement error in beta (see Litzenberg and Ramaswamy [1979]), the maximum likelihood estimators are consistent simply because MLE takes care of measurement error in beta.

In Table 2, the coefficients in the NS regression of OLS, GLS and MLE are obviously characterized by much larger standard errors so that they lose any significance shown in the OLS stationary regression.[5] However, different estimated betas cause little changes in return-risk relationships. From the results of the OLS stationary method, there exists a significant return-risk relationship in subperiod 1, but not in subperiod 2 in both MIMIC and market models. The poor return-risk relationship in subperiod 2 may be due to the poor performance of the CAPM in determining a pricing relation. In the next section, the APT will be used to examine an alternative pricing relationship. Even though the null hypothesis of the CAPM that $a_0 = 0$ cannot be rejected at the 5% level in all four cases, all coefficients are positive. In addition, the intercept in subperiod 2 is too high. It is about 4.3%

annual rate. This is consistent with prior tests of the traditional version of the CAPM.

All nonstationary estimates of a_0 and a_1 in OLS, GLS and MLE in Table 2 are insignificant. Because of the low test power for all nonstationary procedures (the standard errors are too high), in the following, only the magnitudes of the estimated coefficients are discussed. The MLE and GLS estimates of a_0 are much lower and much closer to zero than the corresponding OLS estimates in all four cases. In addition, the MLE estimates of a_1 is greater than the corresponding GLS estimates and is closer to the realized market risk premia in all four cases. The realized market risk premia are 0.751% and 0.636% monthly for period 1 and 2, respectively. This evidence proves that the MLE estimator in the return-risk cross sectional regressions is more appropriate than OLS or GLS estimator in testing the CAPM.

In sum, we have proposed an alternative estimator of betas by the MIMIC model in which measurement error in a market portfolio is allowed. Nevertheless, this reasonable alternative method does not gain much from the traditional OLS estimator. However, some interesting results have surfaced. This evidence supports Stambough's conclusion that the tests of the CAPM are insensitive to different market indexes. In return-risk cross sectional regressions, our evidence shows that the MLE estimator is more appropriate than the OLS or GLS estimator due to measurement error in beta. From these two interesting results, we conclude that measurement error on beta is more serious than measurement error on the market portfolio in testing the CAPM.

IV. Tests of the APT by MIMIC Approach

This section tests the APT using the MIMIC model demonstrated in Section II. The objective is to investigate that: (i) the proper number of factors are used to explain the data, and (ii) the relationships between factors and indicators which are measured by macroeconomic variables. The same nineteen industry portfolios described in previous section are used here. The macroeconomic variables are selected from those most likely related to common stock returns. In the following, the indicators selected in this study will be discussed.

IV.1 Macroeconomic Variables as the Indicators

In early 1970s, several papers attempt to employ economic methods to investigate the relationship between money supply and aggregated common stock prices. Models developed by Keran [1971], Homa and Jaffee [1971] and Hamburger and Kochin [1972] appear to have met with considerable success in explaining the behavior of Standard & Poors Composite Index. However, Pesando [1974] re-examined the above models using different periods. He found that the extraordinary success of these methods in tracking the behavior of stock prices during the sample period may be illusory. We believe that the above spurious regression phenomenon results from ignoring the autocorrelated errors in time series regression equations as pointed out by Granger and Newbold [1974]. Gargett [1978] used a qualitative method to study the relationship between these two variables. He discovered that the Dow Jones Industrial Index follows changes in money supply with a lag of three months.

The relationship between stock returns and inflation has been extensively studied. In particular, Bodie [1976], Nelson [1976] and Fama and Schwert [1977] all present evidence that monthly returns to NYSE Composite Index are negatively related to the inflation rate as indicated by the Consumer Price Index (CPI) since 1953. Cohn and Lessard [1981], Gultekin [1983] and Solnik [1983] also found that stock prices are negatively related to nominal interest rate and inflation in a number of countries. Fama [1981] suggests a reason why the stock market reaction to unexpected inflation is weak. He argues that unexpected inflation is contemporaneously correlated with unexpected movements in important "real" variables, such as capital expenditures or real GNP, so that the correlation between stock returns and unexpected inflation is spurious. After extensively re-examining the relationship between the stock returns and inflation, Geske and Roll [1983] conclude that only Nelson's [1979] and Fama's [1981] money demand explanation is logically consistent but it seems unable to fully explain all of the empirical phenomena. Therefore, Geske and Roll have proposed the fiscal and monetary explanation. They have argued that the basic underlying relation is between stock returns and changes in inflationary expectations.

In exploring the common stocks as hedges against the investment opportunity sets, Schipper and Thompson [1981] selected two candidates for state variables. They are price level as measured by Consumer Price Index (CPI) and the real gross national product less corporate profit (GNP). They found that hedge portfolios offer meaningful hedging potential in portfolio-formation period. In addition, the CAPM or the market model indicates that the return on a security or a portfolio most likely co-move with the return on the market portfolio.

In summarizing, the variables most likely correlated with a stock return would be classified as five categories: (1) money supply, (2) real production, (3) inflation, (4) interest rate, and (5) market return. Further, Brigham [1982] decomposes a risk premium into maturity risk premium and default risk premium. Thus, these two indicators are also included in our study. According to the above discussion, the following 11 variables are selected as the indicators.

1. Return on the market portfolio (RM): the return on NYSE common stock composite index.

2. Transaction volume (VL): the change rate in the transaction volume (shares) for all of the NYSE common stocks.

3. Real riskless rate (RF): the real interest rate on 3-month Treasury bills.

4. Maturity risk premium (MP): the difference between the real interest rates on long-term Treasury bonds (ten or more years) and on 3-month Treasury bills.

5. Default risk premium (DP): the difference between the real interest rates on new AA corporate bonds and on 3-month Treasury bills.

6. Consumer price index inflation rate (CPI): the change rate in urban consumer price index for all items.

7. Money supply (M2): the real change rate in money stock as measured by M2 (M1 + time deposits).

8. Velocity of money supply (PI/M2): the ratio of personal income to money supply M2. This is an alternative measure of money supply.

9. Real industrial production (IP): the change rate in real total industrial productions.

10. Real auto production (IPA): the change rate in real automotive products.

11. Real home production (IPH): the change rate in real home goods.

Since the automobile and housing industries generally lead the rest of the economy, the last two indicators, IPA and IPH, are used to catch up the first two biggest industries. The reason to select industrial production instead of GNP in this study is that all other indicators are published monthly while GNP is published quarterly. Since the industrial production is a very good proxy for GNP, we sacrifice GNP measure to gain the number of time periods.

IV.2 Empirical Results

After carefully selecting the indicator candidates, the time lag or leading problem needs to be solved. The correlation coefficients between the market portfolio return and the other indicators with lags and leadings of zero to five months for both periods were examined. All indicators are contemporaneously correlated with the market portfolio except three real production indicators. The real production indicators follow the market portfolio return with a lag of two or three months. Therefore, in this study, all indicators are contemporaneous except three real production indicators which is two-month lag.

Before the APT is directly tested by the MIMIC model, factor analysis is preliminarily used to determine the number of factors in both periods. Table 3 shows the eigenvalues as a percentage of the first eigenvalue. Clearly, it is only one factor in period 1, while it is perhaps two factors in period 2 by "scree" test described in Chapter 4 of Wei [1984].[6] Consequently, at most a two-factor model is enough to explain the historical data. Three alternative MIMIC models are proposed to test the APT: (i) one-factor eleven-indicator model, (ii)

Table 3

Eigenvalue as a percentage of the first eigenvalue for 19 industry portfolios: 1963-1982*

Panel A: Period: 1963-1972

Factor	PRC	ALP	SCF	ULS
1	100%	100%	100%	100%
2	3.8	4.4	3.9	2.9
3	3.1	1.5	2.6	1.7
4	2.1	1.0	2.3	0.8
5	1.9	0.7	2.0	0.7
6	1.6	0.6	1.9	0.6

Panel B: Period: 1973-1982

Factor	PRC	ALP	SCF	ULS
1	100%	100%	100%	100%
2	7.9	6.9	7.1	7.2
3	2.1	2.8	2.9	1.8
4	1.3	1.0	1.9	0.9
5	1.0	0.6	1.6	0.5
6	1.0	0.4	1.4	0.4

* PRC = principal component analysis
ALP = alpha factor analysis
SCF = simple common factor analysis
ULS = unweighted least squares method

one-factor six-indicator model, and (iii) two-factor six-indicator model. When the two one-factor models are used to test the APT in period 1, there is little difference between eleven-indicator and six-indicator model. Thus, only six indicators are used in the two-factor model to save the computer time.[7]

The structural coefficients of the APT in the MIMIC model for period 1 are reported in Table 4a. In both one-factor models, only the stock market related variables, the market return (RM) and the transaction volume (VL), are significant at the 5% level. From this evidence, if the pricing relation in period 1 is a one-factor APT, this common factor would be most likely related to only the stock market related indicators, namely, the market portfolio return and the transaction volume. Other indicators may be correlated with this single common factor, but they are obviously not as important as the stock market related indicators. Now, let us closely examine other indicators with an absolute t-value of greater than one for eleven-indicator model. The real riskless interest rate (RF), CPI inflation rate (CPI) and the real auto production (IPA) are negatively correlated with this common factor, while the velocity of money supply (PI/M2) is positively related to this common factor. If we regard this common factor as a proxy of market portfolio because most of the weight is on the market portfolio, then, except for real auto production, this evidence supports previous studies done on the relationship between common stock returns and other indicators (Keran [1971], Homa and Jaffee [1971], Hamburger and Kochin [1972], Pesando [1974], Bodie [1976], Nelson [1976], Fama and Schwart [1977] and others). However, there is no previous study which examines the relationship between stock returns and the real auto production.

Table 4a

Structural coefficients of the APT in the MIMIC model
Period 1: 1963-1972

$$\tilde{r}_i = b_{i1}\,\tilde{f}_1 + b_{i2}\,f_2 + \tilde{u}_i,\quad i=1,\ldots,19$$

$$\tilde{f}_j = a_{j1}\,(RM) + a_{j2}\,(VL) + a_{j3}\,(RF) + a_{j4}\,(MP) + a_{j5}\,(DP) + a_{j6}\,(CPI) + a_{j7}\,(M2) + a_{j8}\,(PI/M2) + a_{j9}\,(IP) + a_{j10}\,(IPA) + a_{j11}\,(IPH) + \tilde{e}_j,\quad j=1 \text{ or } 1,2.$$

	a's Coefficients			
	one-factor 11-indicator	one-factor 6-indicator	two-factor 6-indicator	
Indicator	f1	f1	f1	f2
RM	0.908(8.08)*	0.925(7.55)*	0.923(8.85)*	
VL	0.040(2.55)*	0.043(2.60)*	0.040(2.28)*	
RF	-17.24(-1.2)	-3.451(-.76)		-0.300(---)
MP	-15.84(-.90)			
DP	1.693(.12)			
CPI	-16.51(-1.2)	-4.596(-1.1)		-0.119(-.12)
M2	0.039(.03)	-0.344(-.31)		0.458(0.58)
PI/M2	22.23(1.29)			
IP	0.141(.20)	-0.469(-1.1)		-0.054(-.06)
IPA	-.078(-1.3)			
IPH	0.189(.92)			
R-square	.5611	.5412	.5912	.0774

	b's Coefficients			
	one-factor 11-indicator	one-factor 6-indicator	two-factor 6-indicator	
Industry	f1	f1	f1	f2
1	1.000(---)	0.974(12.1)*	1.000(---)	0.410(. 06)
2	0.834(16.5)*	0.812(13.6)*	0.857(16.3)*	-.555(-.06)
3	1.210(16.2)*	1.178(13.4)*	1.211(16.1)*	0.390(-.06)
4	1.020(14.7)*	0.993(12.5)*	1.059(14.4)*	-1.075(-.06)
5	0.939(17.4)*	0.914(14.1)*	0.942(17.4)*	0.270(.06)
6	0.785(10.5)*	0.764(9.62)*	0.831(10.3)*	-1.575(-.06)
7	1.097(15.3)*	1.068(12.9)*	1.122(15.2)*	-.555(-.06)
8	1.183(15.8)*	1.151(13.2)*	1.190(15.7)*	0.120(.05)
9	1.146(18.1)*	1.115(14.4)*	1.126(17.6)*	1.205(.06)
10	1.221(18.2)*	1.188(14.5)*	1.192(17.4)*	1.670(.06)
11	1.389(16.6)*	1.352(13.6)*	1.335(15.0)*	2.875(.06)
12	1.264(17.7)*	1.231(14.2)*	1.236(17.0)*	1.675(.06)
13	1.302(17.2)*	1.268(13.9)*	1.268(16.2)*	1.995(.06)
14	1.218(13.2)*	1.186(11.5)*	1.215(13.0)*	0.485(.06)
15	1.435(14.0)*	1.396(12.1)*	1.405(13.5)*	1.760(.06)
16	0.463(7.66)*	0.450(7.30)*	0.527(7.33)*	-2.340(-.06)
17	1.094(14.1)*	1.065(12.2)*	1.112(14.1)*	-.265(-.06)
18	1.078(16.5)*	1.050(13.6)*	1.094(16.4)*	-.180(-.06)
19	1.012(14.7)*	0.985(12.5)*	1.056(14.3)*	-1.260(-.06)

*significant at the 5% level

Some might argue that weak relationship between non-stock market indicators and the common factor is due to multicollinearities among the indicators. Therefore, six of the eleven indicators are selected to represent each category indicator. They are the market portfolio return (RM), the transaction volume (VL), real riskless interest rate (RF), CPI inflation rate (CPI), money supply (M2) and the real total industrial production (IP). This is the one-factor six-indicator model. The result of this model is shown in Table 4a column 2. The result of this one-factor six-indicator model is very close to that of the one-factor eleven-indicator model. As mentioned before, only the stock market related indicators are significantly correlated with the common factor. Real riskless interest rate, inflation, money supply, and real production are all negatively but insignificantly related to the common factor. For factor equation, the 11-indicator model has only a little high R-square than the 6-indicator model. They are 0.5611 and 0.5412 respectively. Comparing the betas of these two one-factor models in Table 4a, they are very highly correlated with a correlation coefficient of about 1.000. In addition, the average R-square of each return equation in both one factor models is the same with a value of 0.811. Up to this point, there is not much difference between the one-factor eleven-indicator and the one-factor six-indicator models. Later on, the cross sectional regression will be used to double check this result.

Even though we have already discussed that the appropriate model is a one-factor model for period 1 by the scree test of factor analysis, we want to use a two-factor model to double check whether the second factor is significant or not. A predetermined two-factor six-indicator model will be used to test the APT. Factor analysis is employed to classify these six indicators into 2 groups. The first group includes the market portfolio and the transaction volume, while the second group includes other four indicators, real riskless interest rate (RF), inflation rate (CPI), money supply (M2) and real total industrial production (IP). The two-factor result shown in Table 4a columns 3 and 4 displays that only the first factor is significantly related to RM and VL. Whereas the second factor is very insignificantly correlated with the second group indicators. This is also evident by examining from the second betas in the Table. All of the second betas are insignificant. Furthermore, the first beta coefficient is very highly correlated with the betas in both one-factor models with both correlation coefficients of 0.996. This is further supported by the R-square criteria. The average R-square of each return equation in the one-factor model is 0.811, while 0.844 in the two-factor model. If the adjusted R-square is used as the criteria, the increase in R-square will be insignificant. Thus, a one-factor APT is good enough to explain the first period data. We will reconfirm this argument by the cross sectional regression.

Table 5 Panel A reports the return-risk cross sectional relationship in period 1 for the APT in the MIMIC model. Both one-factor models have a very similar result. Their adjusted R-squares are the same of 0.258. The intercepts are both insignificantly different from zero but positive (recall that the LHS variable is excess return). The factor risk premia for both one-factor models are positive and significant. This is exactly the result that should have been concluded

Table 4b

Structural coefficients of the APT in the MIMIC model
Period 2: 1973-1982

$$\tilde{r}_i = b_{i1}\tilde{f}_1 + b_{i2}\tilde{f}_2 + \tilde{u}_i, \quad i=1,\ldots,19$$

$$\tilde{f}_j = a_{j1}(RM) + a_{j2}(VL) + a_{j3}(RF) + a_{j4}(MP) + a_{j5}(DP) + a_{j6}(CPI) + a_{j7}(M2) + a_{j8}(PI/M2) + a_{j9}(IP) + a_{j10}(IPA) + a_{j11}(IPH) + \tilde{e}_j, \quad j=1 \text{ or } 1,2.$$

a's Coefficients

Indicator	one-factor 11-indicator	two-factor 6-indicator	
	f1	f1	f2
RM	0.859(6.38)*	1.000(6.67)*	
VL	0.073(3.34)*	0.075(2.83)*	
RF	-5.586(-1.1)		-5.600(---)
MP	-2.254(-.40)		
DP	-7.417(-.70)		
CPI	-9.786(-1.6)*		1.566(.32)
M2	-1.820(-1.2)		1.810(0.72)
PI/M2	28.60(1.16)		
IP	-.290(-.42)		
IPA	-.142(-1.6)*		-0.368(-1.7)*
IPH	0.065(.20)		
R-square	.5811	.5525	.1836

b's Coefficients

Industry	one-factor 11-indicator	two-factor 6-indicator	
	f1	f1	f2
1	0.845(8.85)*	0.993(7.86)*	0.502(1.95)*
2	0.786(13.4)*	0.724(8.39)*	-.184(-1.7)*
3	1.073(13.3)*	0.948(7.98)*	-.379(-1.9)*
4	0.884(13.2)*	0.850(14.4)*	-.081(-1.0)
5	0.829(13.5)*	0.804(8.81)*	-.054(-.77)
6	0.676(7.96)*	0.797(7.41)*	0.408(1.93)*
7	1.026(14.2)*	0.948(8.62)*	-.218(-1.7)*
8	0.898(12.4)*	0.896(8.67)*	0.029(.38)
9	1.083(14.8)*	1.026(8.97)*	-.146(-1.4)
10	1.082(14.5)*	1.054(9.11)*	-.053(-.63)
11	1.171(14.7)*	1.098(8.87)*	-.192(-1.6)
12	1.139(14.4)*	1.058(8.72)*	-.222(-1.7)*
13	1.188(14.7)*	1.115(8.86)*	-.208(-1.6)
14	0.850(11.0)*	0.869(8.33)*	0.089(0.99)
15	1.186(13.0)*	1.088(8.21)*	-.288(-1.7)*
16	0.534(9.76)*	0.506(7.32)*	-.076(-1.2)
17	1.122(12.8)*	0.961(7.55)*	-.506(-2.0)*
18	1.113(14.3)*	1.001(8.40)*	-.341(-1.9)*
19	1.042(13.1)*	0.959(8.29)*	-.242(-1.7)*

*significant at 5% level

from the APT. On the other hand, the intercept in the two-factor model is much higher than those in the one-factor models, and the two factor risk premia are both insignificant.[8] The adjusted R-square is a little lower than those in the one-factor models. From the results of the MIMIC model and the cross sectional regressions, it is probable that one-factor APT with the market portfolio and the transaction volume as the determinants of the single factor is the appropriate pricing model for period 1. Comparing the MIMIC CAPM and the CAPM in Table 2 with this one-factor model, the MIMIC CAPM is closer to the one-factor model. In addition, the factor risk premium is closer to the realized market risk premium than that in the MIMIC CAPM model.

Now, let us examine the APT in period 2. The structural coefficients of the APT in the MIMIC model for period 2 are represented in Table 4b. Because six indicators do not make much difference from eleven indicators in the one-factor model in period 1, only the eleven-indicator model is used to test the APT for the one-factor model in period 2 in order to save the computer time. From the one-factor model, the result is similar to that in period 1. The stock market return and the transaction volume are the most significant indicators. However, inflation and the real auto production are also significant even just at the marginal level. This reinforces our suspicion that there may be more than one factor in period 2. Let us closely examine the indicators with an absolute t-value greater than one. Real interest riskless rate, inflation, money supply and real auto production are all negatively correlated with the common factor, while the velocity of money supply is positively correlated with this common factor. Overall, this result

Table 5

Return-risk cross section relationships of the APT in the MIMIC model: 1963-1982

$$\overline{R}_i = \hat{a}_0 + \hat{a}_1 b_1 + \hat{a}_2 b_2 + \tilde{e}_i, \quad i=1,\ldots,19.$$

Model	$\hat{a}_0$	$\hat{a}_1$	$\hat{a}_2$	$\overline{R}^2$
	Panel A: Period 1, 1963-1972			
one-factor 11-indicator	0.159 (0.710)	0.543* (2.693)		0.258
one-factor 6-indicator	0.159 (0.710)	0.558* (2.692)		0.258
two-factor 6-indicator	0.507 (1.219)	0.206 (0.529)	0.071 (1.221)	0.257
	Panel B: Period 2, 1973-1982			
one-factor 11-indicator	0.370 (1.328)	0.285 (0.967)		-0.002
two-factor 6-indicator	0.040 (0.150)	0.684* (2.377)	0.362* (2.066)	0.215

Note: The average monthly returns are multiplied by 100 before regressing.

again supports previous studies. Now, let us turn to the two-factor six-indicator model. Follow the same procedures done for period 1. The result is displayed in Table 4b columns 2 and 3. The market portfolio (RM) and the transaction volume (LV) is significantly related to the first factor. However, the real auto production is significantly correlated with the second factor this time even only at the marginal level. Comparing other indicators with those in period 1, real riskless interest rate is again negatively related to the second factor, but inflation rate and money supply are positively related to the second factor in the period. From the result of the relationship between the factors and the indicators, the second factor is still important even though less important than the first factor for period 2. This can also be checked by the significance of betas in Table 4b. Ten out of the 19 second factor betas are significant although the relationship is not as strong as those in the first factor betas. Because the first factor is correlated with stock market related indicator, this factor can be regarded as a proxy of the market portfolio. The correlation coefficient between the beta in the first factor and the beta in the MIMIC CAPM is very high with a coefficient of 0.923. Further the average R-square of each return equation in the one-factor model is 0.818, while 0.885 in the two-factor model. When the adjusted R-square is used as a criteria, the increase in R-square should not be trivial and will be significant. In addition, the R-square for the second factor equation is as high as 0.1836. All of these results indicate that the second factor should be important. We further check whether the second factor is important or not by the cross sectional regression.

The risk-return cross sectional relationship of the APT in the MIMIC model for period 2 is shown in Table 5 Panel B. For the one-factor model, both the intercept and the factor risk premium are insignificant. And the intercept is too high with an annual rate of 4.3%, while the factor risk premium is far below the realized market risk premium with a monthly rate of 0.636%. The adjusted R-square is negative. On the other hand, the intercept for the two-factor model is insignificant and very near to zero, while the two factor premia are significant with the first factor premium very close to the realized market risk premium. The adjusted R-square is as high as 0.215. The results of the APT in the MIMIC model confirm the scree test of the factor analysis and the poor performance of the CAPM in previous section for period 2. Furthermore, comparing the result in Table 5 Panel A with that in Table 2, we can conclude that the two-factor APT outperforms the one-factor APT, the MIMIC CAPM and the CAPM in period 2. But the one-factor APT does a better job than the two-factor APT in period 1, and there is not much difference among the one-factor APT, the MIMIC CAPM and the CAPM. This evidence supports Ross's argument that the APT is more general than the CAPM because the APT allows more than one factor in the pricing relation.

It will be interesting to see what will happen, if market variables (the market portfolio and transaction volume) are excluded from the model. Table 6 shows the structural coefficients of the one-factor APT without market variables.[9] The b coefficients (factor loadings) shown in Table 6 for both periods are very close to those estimated from the one-factor APT with market variables shown in Tables 4a and 4b respectively.[10] However, the results from the factor equation have dramatically changed.

Table 6

Structural coefficients of the one-factor APT in the MIMIC model without market variables: 1963-1982

$$\tilde{r}_i = b_{i1}\tilde{f}_1 + \tilde{u}_i, \quad i=1,\ldots,19$$

$$\tilde{f}_1 = a_1(RF) + a_2(MP) + a_3(DP) + a_4(CPI) + a_5(M2) + a_6(PI/M2) + a_7(IP) + a_8(IPA) + a_9(IPH) + \tilde{e},$$

Indicator	a's Coefficients 1963-1972	a's Coefficients 1973-1982
RF	-25.541(-1.26)	-18.666(-3.39)*
MP	-26.061(-1.18)	-1.067(-0.17)
DP	-4.350(-0.23)	-30.745(-2.68)*
CPI	-25.989(-1.32)	-23.146(-3.52)*
M2	3.652(1.85)*	-1.630(-0.98)
PI/M2	45.126(1.91)*	110.380(4.22)*
IP	-0.932(-0.97)	0.124(0.16)
IPA	0.046(0.57)	0.214(2.18)*
IPH	0.298(1.06)	-.120(-.33)
R-square	.0611	.3915

Industry	b's Coefficients 1963-1972	b's Coefficients 1973-1982
1	1.000(---)	1.000(---)
2	0.833(16.45)*	0.930(10.10)*
3	1.209(16.20)*	1.270(10.03)*
4	1.019(14.70)*	1.045(9.99)*
5	0.939(17.43)*	0.981(10.11)*
6	0.785(10.53)*	0.800(9.64)*
7	1.097(15.33)*	1.214(10.41)*
8	1.183(15.79)*	1.063(9.64)*
9	1.146(18.11)*	1.283(10.63)*
10	1.221(18.25)*	1.282(10.53)*
11	1.389(16.58)*	1.386(10.60)*
12	1.265(17.74)*	1.349(10.50)*
13	1.302(17.16)*	1.407(10.63)*
14	1.218(13.19)*	1.006(8.96)*
15	1.436(14.05)*	1.404(9.92)*
16	0.463(7.66)*	0.632(8.23)*
17	1.094(14.13)*	1.329(9.84)*
18	1.078(16.46)*	1.318(10.47)*
19	1.012(14.70)*	1.233(9.95)*

*significant at the 5% level

For period 1, the R-square is only 0.0611 which is much lower than 0.5611 from the one-factor APT with market variables. This result indicates that the market variables play the major role in the pricing behavior during period 1. When the market variables excluded from the model, among nine indicators, only the two money supply variables, M2 and PI/M2, are positively related to the unique common factor at the marginal level. For period 2, the R-square of the factor equation for the model without market variables is 0.3915 which is higher than the one in period 1. This evidence denotes that, in addition to the market variables, some other macroeconomic indicators play a relatively important role in the pricing behavior during period 2. Among the nine non-market variables, real risk-free rate (RF), default risk premium (DF) and inflation (CPI) are significantly negatively related to the common factor, while the velocity of money supply (PI/M2) and the real auto production (IPA) are significantly positively related to the common factor. All of the relationships are as we expect. The results from the model without market variables also confirm our previous evidence that the 1963-72 data can be described by a one-factor APT with the market variables as its indicators, while the 1973-82 data should be explained by more than one factor APT.

V. Conclusion Remarks

This paper tests the CAPM and the APT using a MIMIC approach. The results support the conclusion that the APT outperforms the CAPM, especially for period 2. The beta estimated from the MIMIC model by allowing measurement error on the market portfolio does not significantly improve the OLS beta. However, the MLE estimator does a better job than the OLS and GLS estimators in the cross sectional regressions because the MLE estimator takes care of the measurement error in beta. Therefore the measurement error on beta is more serious than measurement error on the market portfolio. This evidence supports Stambough's [1982] argument that the inference about the tests of the CAPM is insensitive to alternative market indexes. When the one-factor APT with market variables is compared with the model without market variables, we found that the market variables play a major role in pricing behavior. Therefore, we conclude that it is inappropriate for the study of the relationship between the common factors extracted from the APT and the macroeconomic variables without including the market variables.

Footnotes

1. Fogler, John and Tipton [1981] and Chen, Roll and Ross [1983] indirectly link the factors extracted from the APT to economic indicators. Joreskog and Goldberger [1975] have shown that this kind of indirect estimation method is not as efficient as the direct estimation method to be explored in this section.

2. Here, we use different terminologies in defining the factors and indicators compared with those used in traditional MIMIC model.

3. The terminologies stationary OLS and nonstationary OLS have been used by Friend and Westfield [1980]. The GLS and MLE methods have been discussed by Litzenberger and Ramaswamy [1979].

4. The groups used here is the same as Stambough's. The last group used in MacBeth and in Schipper and Thompson is dropped, because it is heterogeneous.

5. The similar results were also found in the Friend and Westfield's [1980] study of co-skewness.

6. In his dissertation, Wei [1984] has shown that the "scree" test is a powerful test in identifying the number of relevant factors in the APT. By using simulation study, Wei has shown that Roll and Ross's [1980] ML method in estimating factors are inferior to methods listed in table 3.

7. It is very expensive to run LISREL program, especially for more than two factor models.

8. The loss of the significance of the first factor risk premium is due to the multicollinearity problem.

9. Only the one-factor APT is used to investigate the difference between the models shown in Table 4 and in Table 6.

10. If we normalize the one-factor 11-indicator model for period 2 shown in Table 4b by setting $b_1 = 1.00$, it is easily seen that the b coefficients of one-factor model shown in Table 4b and Table 6 column 2 are very similar.

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